Analyzing the effect of cosmetic essence by independent component analysis for skin color images

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Abstract

In development of cosmetic essence, measurement of melanin distribution is required to evaluate the effect of cosmetic essences. However, exact measurement of the melanin distribution is very difficult because it is affected by other pigmentations. In this paper, the decrease of melanin component is analyzed by extracting the melanin distribution from digital color images. The independent component analysis (ICA) is used to extract the melanin component from the color images. The ICA is a technique that extracts the original signals from mixtures of many independent sources without *a priori* information on the sources and the process of the mixture. This paper shows that proposed method is effective to observe the change of the melanin distribution without influence of other pigmentations.

1 Introduction

In the field of cosmetic industry, the techniques of color engineering are important for designing and evaluating the products. It is expected to evaluate the effect of cosmetic essences by the techniques of color engineering. In Japan, whitening essences are widely used in women. They are used to decrease the freckle on the face of Japanese; Mongoloid. The freckle is a concentrated melanin in the epidermis layer of the skin. In the development of whitening essence, measurement of melanin distribution is required to evaluate the effect of whitening essences. However, exact measurement of the melanin distribution is very difficult because the measurement is affected by other pigmentations.

In this paper, the decrease of melanin component is analyzed by extracting the melanin distribution from digital color images. The independent component analysis (ICA) [1-5] is used to extract the melanin component from the color images. The ICA is a technique that extracts the original signals from mixtures of many independent sources without *a priori* information on the sources and the process of the mixture. In our previous paper [6,7], we proposed a technique to separate skin color image into the spatial distributions of hemoglobin and melanin components. The separated components of melanin will give effective information for evaluation of whitening essence. An experiment with practical application of essence was performed for 28 female subjects.

In Section 2, we briefly review the independent component analysis. In Section 3, skin color is modeled on the basis of melanin and hemoglobin pigments in the optical density domain. The independent component analysis is applied to the color image separation based on the skin model [6,7]. Experimental results are shown in Section 4.

2 Independent Component Analysis (ICA)

ICA is a technique that extracts the original signals from mixtures of many independent sources without *a priori* information on the sources and the process of the mixture. Observed vector **v** is shown as follows:

$$\mathbf{v} = \mathbf{A}\mathbf{s}, \qquad (1)$$

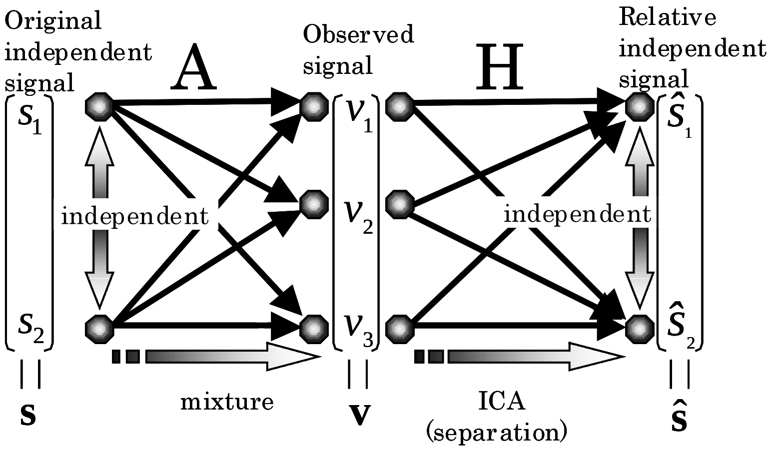


Figure 1: Flow of the signals

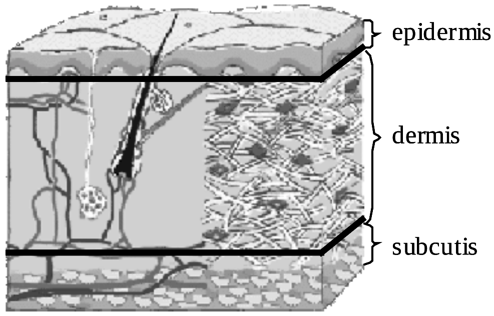


Figure 2: schematic model of human skin

where **s** is source vector, and **A** is $m \times n$ mixing matrix. By applying the ICA to the observed vector, the relative source signals are extracted without a priori information on these items, by assuming that original source signals are mutually independent. In performing ICA, let us define the following equation by using the separating matrix **H** and separated vector $\hat{\mathbf{s}}$: as follows

$$\hat{\mathbf{s}} = \mathbf{H}\mathbf{v}\,,\ \mathbf{H}=[\mathbf{h}_1,\mathbf{h}_2,\ldots,\mathbf{h}_m], \tag{2}$$

where $\mathbf{h}_i$ (i =1,2,…m) are separating vectors. By finding the appropriate separating matrix **H**, we can extract the mutually independent vector $\hat{\mathbf{s}}$ from observed vectors. Figure 1 shows the flow of mixture and separation signals. We use the Fixed Point algorithm [2] to estimate the separating matrix **H**.

The extracted independent signals $\hat{\mathbf{s}}$ correspond to **s**. It is impossible to determine the absolute quantities **s** without an additional assumption. Therefore the extracted independent vector $\hat{\mathbf{s}}$ is given by

$$\hat{\mathbf{s}} = \mathbf{R}\Sigma\mathbf{s}\,, \tag{3}$$

where **R** is the permutation matrix which substitute the elements of the vectors for each other, and Σ is the diagonal matrix that relates the absolute value to the relative value. Substituting Eqs. (1) and (2) into Eq (3) gives

$$\mathbf{HAs} = \mathbf{R}\Sigma\mathbf{s}\,. \tag{4}$$

If we take Eq. (4) in the arbitrary independent vector, the matrix $\mathbf{HA}$ should be equal to the matrix $\mathbf{R}\Sigma$, and mixing matrix **A** is calculated by using the inverse matrix of **H** as follows:

$$\mathbf{A} = \mathbf{H}^{-1}\mathbf{R}\Sigma\,. \tag{5}$$

Note that what we can obtain by ICA are relative value and directions of source vectors. In our application of color image separation, however, the absolute values are not required because we evaluate the ratio of change in this study.

3 Modeling of skin for ICA[6,7]

A schematic model of human skin is shown in Figure 2 with plane-parallel epidermal, dermal, and subcutaneous layers. Various pigments such as melanin, hemoglobin, bilirubin, and β-carotene are contained in the layers; in particular, melanin and hemoglobin are predominantly found in the epidermal and the dermal layer, respectively.

Analyzing skin color, we made four assumptions about skin color. First, the Lambert-Beer law, or rather the modified the Lambert-Beer law [9], holds with respect to the reflected light among the quantities and the observed color signals. Second, the spectral distribution of the skin is not abrupt in the sensitive spectral range of each channel in the imaging system. Third, two pigments cause the spatial variations of color in the skin: melanin and hemoglobin. Fourth, the

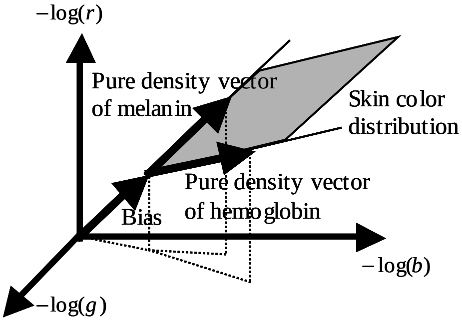


Figure 3: skin color model in the optical density domain of three channels

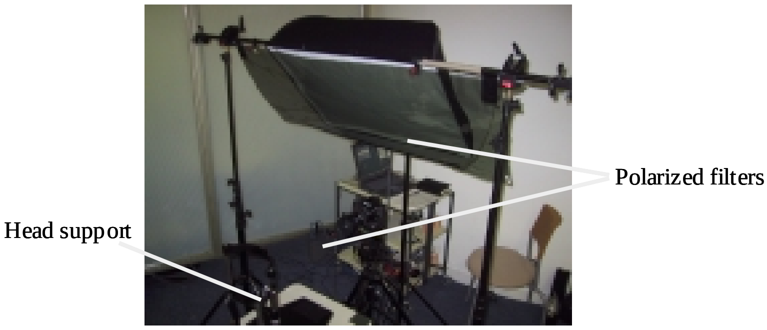
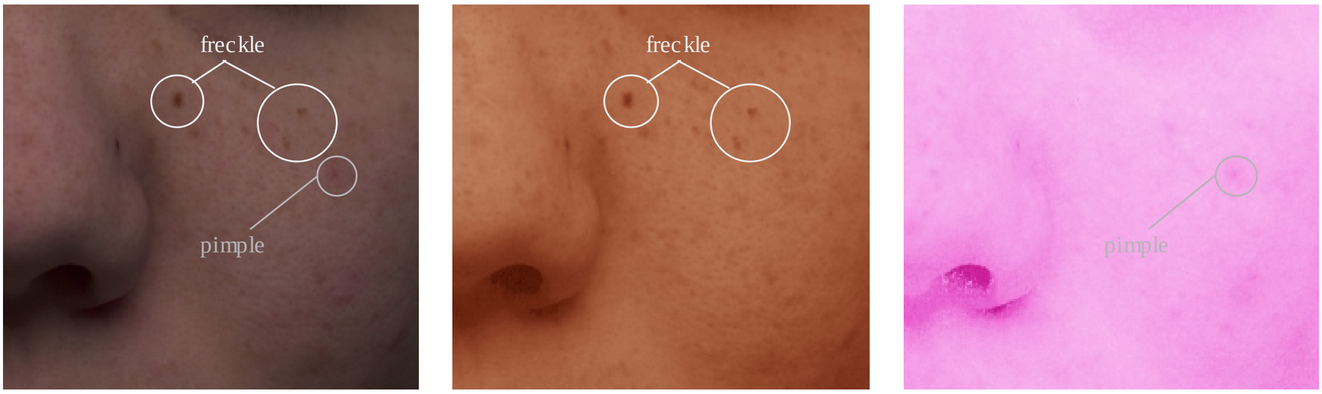


Figure 4: Experimental setup



(a) original image (b) extracted melanin image (c) extracted hemoglobin image

Figure 5: The resultant images captured at beginning of the experiment
(a) Original image, (b) extracted melanin image, (c) extracted hemoglobin image

pigment quantities are mutually independent spatially.

The first assumption ensures linearity among the observed colors signals and pure color signals of the pigments in the spectral density domain. The second assumption ensures linearity in the optical density domain of three channels: $-\log(r^{l,m}), -\log(g^{l,m}), -\log(b^{l,m})$, where ($l$, m) is image coordinate, r, g, b are pixel values for R, G, B channels, respectively. On the basis of the linearity and the third assumption, the color in the skin images is modeled as shown in Figure 3 in the optical density domain of three channels. It is seen that the three densities of skin color are distributed on the two-dimensional plane spanned by the pure color vectors of melanin and hemoglobin. We denote the relation between the color density vector $\mathbf{v}^{l,m}$ and pigment vectors $\mathbf{s}^{l,m}$ as follows, which is the same as Eq. (1)

$$\mathbf{v}^{l,m} = \mathbf{A}\mathbf{s}^{l,m} \tag{6}$$

where **A** denotes the mixing matrix that has pure color vectors of two. By finding separating matrix **H**, as described in section 2, we can extract the mutually independent signals as element vector from the compound color vectors in the image. Figure 5 shows examples of original image and separated images for each pigment. From the resultant images, we confirm the features of pigmentation. The freckle that is a concentrated melanin exists only the melanin image. The pimple that is concentrated hemoglobin exists only in the hemoglobin image.

4 Evaluation of whitening essence

Facial color images of 28 female subjects are captured by digital camera (Nikon D1). Figure 4 shows the experimental setup to capture the images. Polarized filters were set alternately in front of camera and illumination to remove specular light [8]. The heads of subjects were fixed on head support to capture the images of the same point of view during the experiments.

Table 1 Averaged value of changes between the images of beginning and 8 weeks later in the experiment

	melanin	hemoglobin
variation	-2.8%	-4.5%

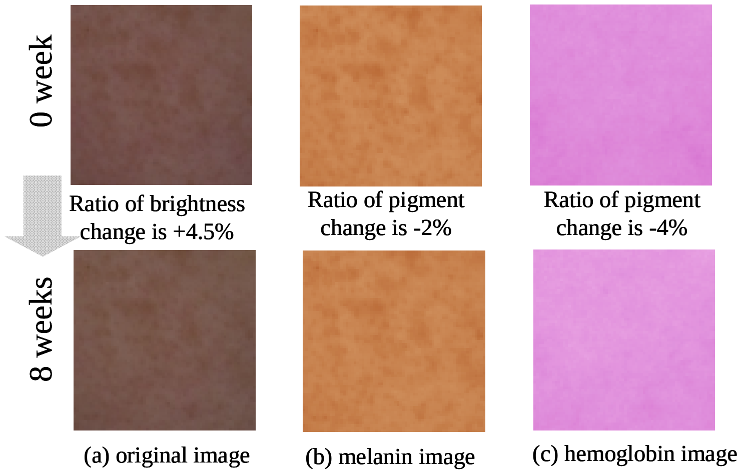


Figure 6: The resultant images of the experiment
(a) original image, (b) melanin image, (c) hemoglobin image

We asked the subjects to apply the whitening essence everyday to their face during 8 weeks. The images were captured at the beginning of the experiments and 2, 4, 8 weeks later. The ICA is applied to all images, and the melanin components are extracted [6,7]. We calculated total amount of pigmentations from separated images and changes for pigmentations between the images of beginning and 8 weeks later in the experiment. Table 1 shows the averaged value of pigmentation changes between the images of beginning and 8 weeks later in the experiment. Figure 6 shows the resultant images of experiments. It is seemed that hemoglobin pigment affects skin color larger than melanin pigment. The amount of hemoglobin depends on physical and mental conditions. Therefore, it is confirmed that proposed technique is very effective to evaluate the change of melanin pigment without influence of hemoglobin pigment.

5 Conclusion

The decrease of melanin component is analyzed by extracting the melanin distribution from digital color images. At this time, the effect is a little because of short term of experiment. However, proposed method could confirm the change of pigmentations and evaluate the effect of whitening essence appropriately. The proposed method can be also applied for analyzing hemoglobin pigment in the medical application.

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